OPSEC REVIEW CERTIFICATION

(AR 530-1, Operations Security)

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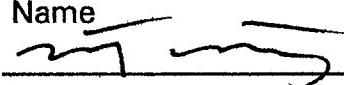
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Monte Carlo Evaluation of an Iterative Technique for the Design of Observer Field Tests

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ABSTRACT

In field tests to compare the observability of combat vehicles, the test designer must select the optimum number of observation opportunities in order to balance collecting enough data to draw valid conclusions against the high cost of supporting vehicles and personnel at a test site. The test designer, however, generally lacks key parameters for the efficient design of the test. Namely, the designer lacks the detection probabilities of the vehicles at each range. The standard deviation of the difference in detection probability depends upon the detection probability itself. Therefore, the test designer must select the number of observations for each range based upon the conservative assumption that the probabilities are near 50%, the probability for the maximum standard deviation. In a previous paper, I presented an iterative technique of test design in order to improve the efficiency of observability tests. In this paper, I present the results of a Monte Carlo evaluation of this iterative technique.

1. THE EXPERIMENTAL SITUATION

Figure 1 illustrates a typical test setup for a test of observability. Observers are stationed at a fixed site and attempt to detect a vehicle in their field of view. For each observation opportunity, the test personnel record the number of detections. In analyzing the data, the analyst groups the observations into range bins and compares the proportion of detections for each test vehicle.

For such a field test, the test designer must select the optimum number of observation opportunities at each range. The designer must balance collecting enough data to draw valid conclusions against the high cost of supporting vehicles and personnel at a test site.

2. DESIGNING THE EXPERIMENT

The test designer selects the number of observations in order to achieve two objectives. First, the number of observations must be large enough so that the probabilities of errors are below the desired level. And, second, the number of observations must be as small as possible to minimize testing time and cost.

Table I illustrates the types of errors that can occur in drawing conclusions from an observation test. The goal of an observation test is to judge whether the observed difference in detection probability, P_d, is unusual enough to reject the null hypothesis that Vehicle A and Vehicle B have the same P_d. If the analyst concludes that the null hypothesis cannot be rejected, then either the analyst has made a correct decision or a Type II error. On the other hand, a decision to reject the null hypothesis will be either correct or a Type I error. In terms of countermeasure effectiveness, a Type I error is an erroneous conclusion than an ineffective countermeasure is effective, while a Type II error miss judges an effective countermeasure.

In a previous paper [1], I discussed the number of observation opportunities required to control the probability of these errors. For the case of an average P_d of 0.5, Figure 2 plots the number of observations required to maintain the

probability of Type I and Type II errors at less than 5%. For example, 85 observations of each vehicle are adequate for an observed 0.15 difference to be significant with less than 5% chance of a Type I error. On the other hand, for less than 5% chance of committing a Type II error when the underlying probabilities differ by 0.15, the requirement is 316 observation opportunities per vehicle.

3. AN ITERATIVE TECHNIQUE FOR TEST DESIGN

In a previous paper [2], I presented an iterative technique to reduce the number of observation opportunities required for a test. Observation data is described by the binary distribution. But the binary distribution has the property that the standard deviation depends upon the probability. If p is the probability and N is the number of trials, then the standard deviation of the number of successes, σ, is given by

$$\sigma = \sqrt{Np(1-p)}$$ (1)

And the standard deviation of the proportion of successes is given by

$$\frac{\sigma}{N} = \sqrt{\frac{p(1-p)}{N}}$$ (2)

Figure 3 plots Equation 2 for an N of 100, 200 and 300. Figure 4 plots the same equation normalized to its maximum at $p = 0.5$.

Figure 5 further shows how the number of trials change with probability if the standard deviation is held fixed. For example, in comparison to a probability of 0.5, only 60% as many trials are need at a probability of 0.1.

To use this property of the binary distribution, the test designer modifies the test matrix as the test progresses. Early test results yield estimates of the probability of detection for each vehicle at each range. Based on these estimates, the test designer reallocates the number of observations among the ranges, improving the efficiency of the test design. Figures 5 and 6 illustrates a sample of the improvement in efficiency that this technique can achieve. Initially the test designer would have selected the number of observations at each test range by assuming the worst-case value of $P_d = 0.5$. But as the test progresses, the designer would use estimates of P_d from the early measures to redesign the test. For example, at range 20, the designer would reduce the number of observations from 314 to 251. Overall in this sample test, the test designer would reduce the number of observations from 1570 to 1193, a reduction of 24%.

4. MONTE CARLO EVALUATION

Simulation of the example of Figures 5 illustrates the speed of convergence of this iterative technique. Figure 7 shows how the number of observations per day at each range would change as the iterative technique is applied. Initially, the assumed 50 observation per day would be divided evenly among the 5 ranges. As the test progresses, more observations would be allotted to the range with a probability of 0.5 and fewer to the other ranges. Figure 8 plots the difference between the adjusted number of runs per day for each range and the number after 100 observations. After 30 observations at each range, the adjustments are minor.

5. CONCLUSION

In this paper, I have presented an iterative technique of using early test results in an observation test to improve the overall efficiency of the test design. Moreover, a simulation showed that the technique yields quickly converging adjusted values for the number of observations at each range based on estimates of probabilities of detection

6. REFERENCES

1. J. G. Bennett, "Use of the Fisher Exact Test for the Design of Observer Tests", *Proceedings of the 2001 Ground Target Modeling & Validation Conference*, Houghton, MI, August 2001.
1. J. G. Bennett, "Techniques for Iterative Design of Observer Field Tests", *Proceedings of SPIE Aerosense 2002*, Orlando, April 2002.

Possible Outcomes of Hypothesis Testing

Decision:	Is Vehicle A Less Detectable Than Vehicle B?	
	No	Yes
Accept Null Hypothesis	Correct	Type II Error
Accept Alternative Hypothesis	Type I Error	Correct

Table 1. Definitions of Type I and Type II errors.

Test with Fixed Observers

Fixed Observers
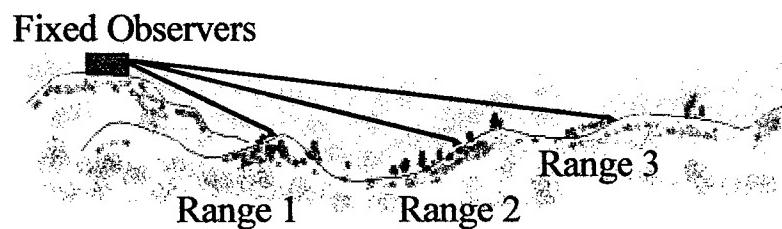
Figure 1. Experimental setup for an observer test.

Number of Opportunities
Required to Meet Test Criteria
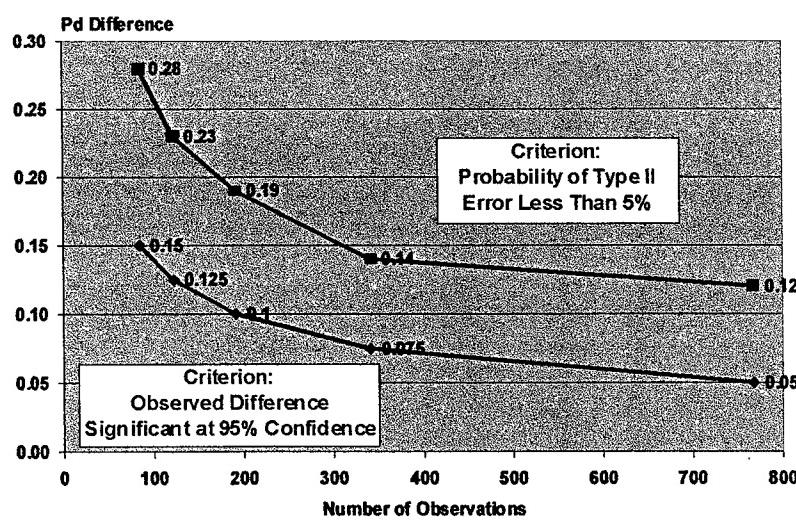
Figure 2. Number of observation opportunities required to meet test criteria.

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Standard Deviation vs. Probability
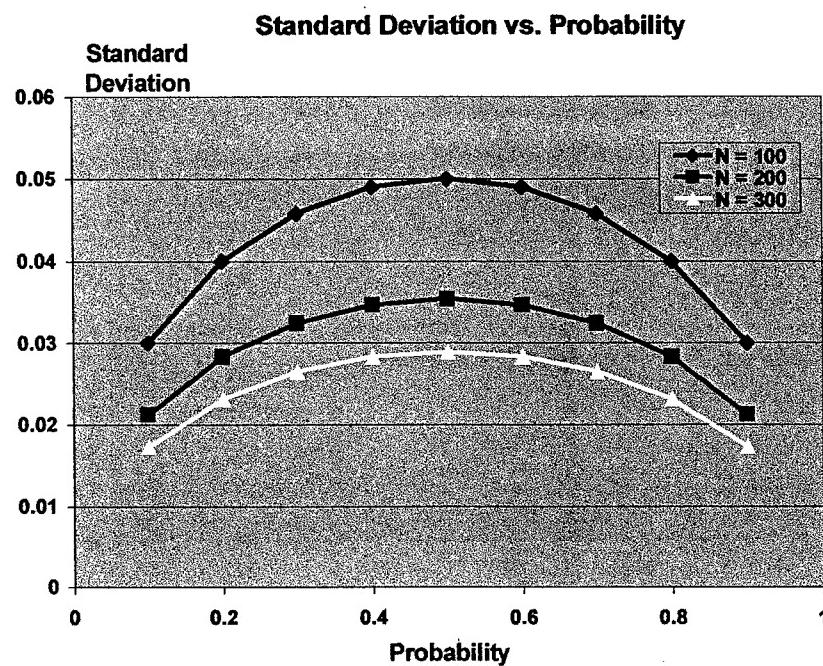
Figure 3. Standard deviation of a binary distribution for 100, 200 and 300 trials.

Number of Observation for Constant Standard Deviation
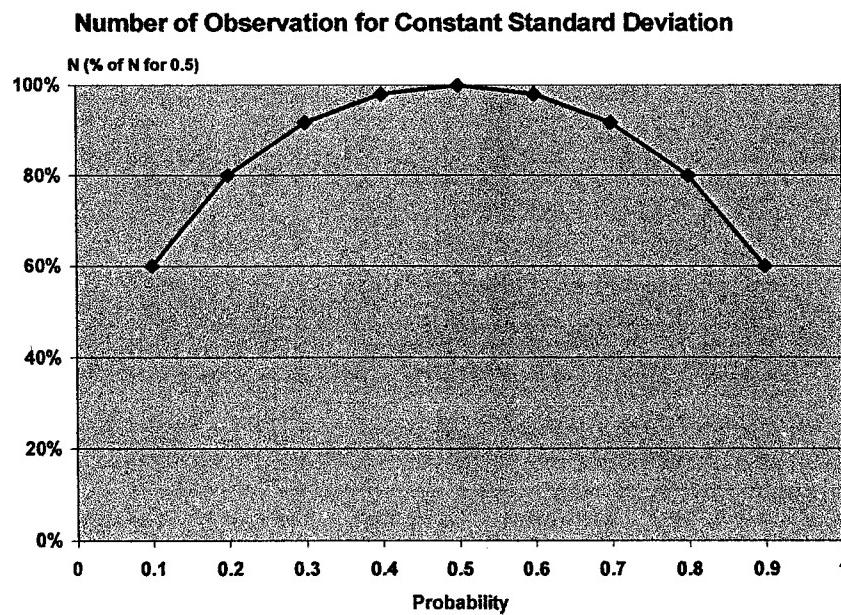
Figure 4. Standard deviation of a binary distribution normalize to probability of 0.5.

Number of Observations per 50 Run Day
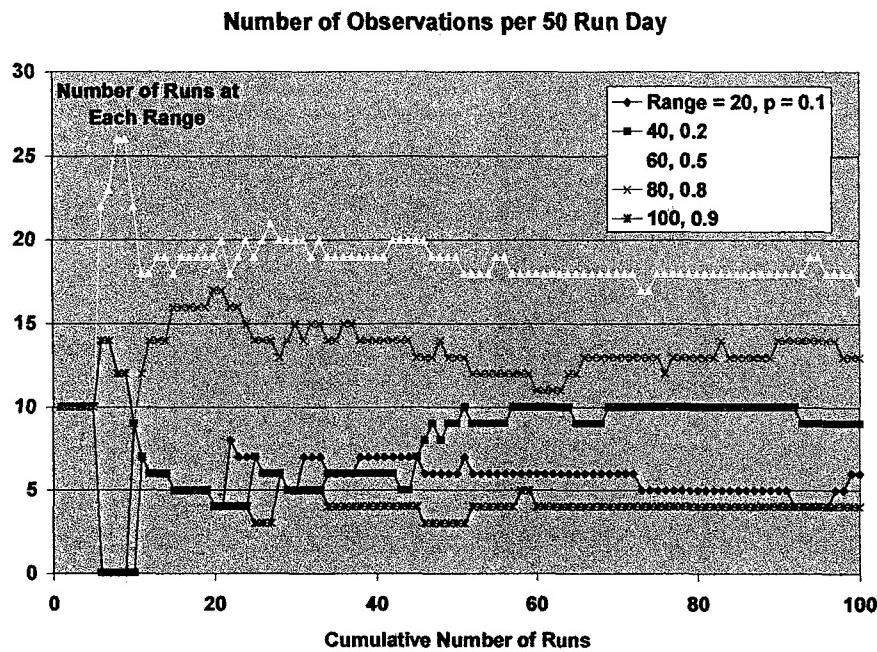

Figure 7. Adjustment of number of observations at each range as sample test progresses.

**Convergence of Number of Runs per Range**
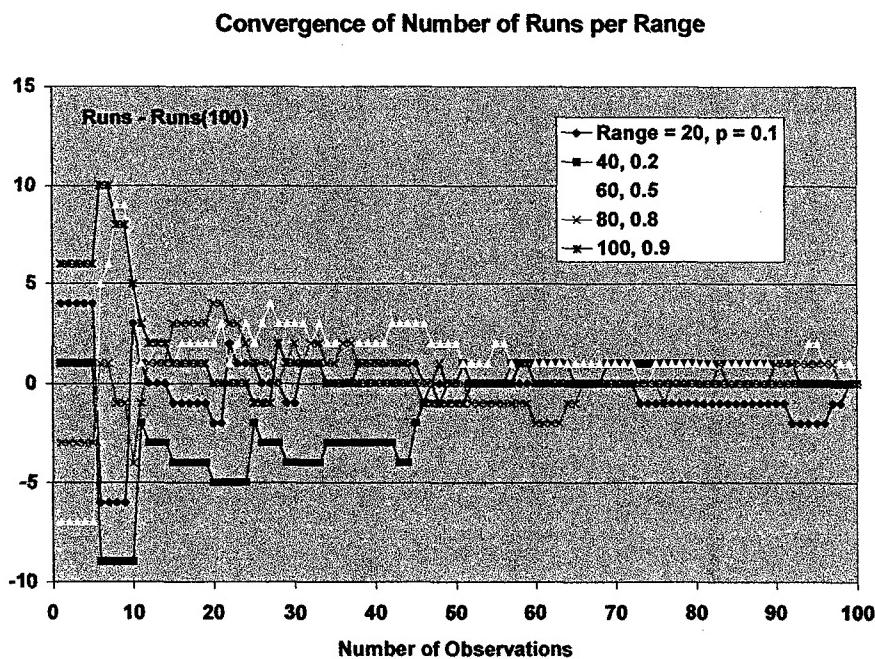
Figure 8. Convergence of the number of observations per day for each range.

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